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ON MAN-COMPUTER INTERACTION: A MODEL AND SOME RELATED ISSUES

Jaime R. Carbonell

Contract No. F19628-68-C-0125
Project No. 8668
Task No. 866800
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Scientific Report No. 1

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Contract Monitor: Hans Zschirnt
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ABSTRACT

A survey of the literature related to man-computer interaction reveals the many aspects of this problem, which appears to be in the crossroads among such diverse fields as computer languages, computer systems operational characteristics, control theory, decision theory, information theory, applied psychology, computer display and interface engineering, etc. In this paper we have chosen to present the on-line interaction from an information and decision point of view. After a brief discussion of classes of on-line situations and tasks, we propose a model of the case in which a human operator is engaged on-line in the solution of a problem like debugging a program, testing a model in a scientific application, or performing a library search. In this model the human operator is considered to seek to minimize overall cost. This cost is obtained by adding the operational cost of both man and computer to a remnant terminal cost originated by the remaining uncertainty. This analysis, performed for each of a set of possible alternatives for action, may lead to select and execute one of them, to terminate the process, or to re-evaluate the possible alternatives and/or hypotheses in a search for new ones. Some practical applications in terms of response time and other characteristics of a computer utility are presented, as well as some theoretical implications from an informational point of view.

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I. PROBLEM DEFINITION

In this paper we present a study on man-computer interaction. Among the many aspects of the problem, we will focus our attention on the interaction process itself studied from a behavioral point of view.

Since people began using computers on-line, interest developed in studying interaction. However, man-computer interaction is a subject with different connotations to different people. To some of them, it means discussing the present applications and future possibilities of man-computer symbiosis (1-3); to others it suggests the development of complete hardware and/or software systems or subsystems (4-9). Some people will immediately think of computer languages (10,11), others will focus on the perceptual aspects of the problem (12).

We want here to discuss and model (as much as possible in mathematical terms) what a human operator (HO in the following) does when he is sitting in front of a console of a time-sharing system, how he inputs a problem, observes results, and makes decisions conditional upon those results and other factors; how he is affected by either intrinsic or operating system characteristics, etc. Why center our attention on this aspect of the problem of man-computer interaction instead of more concrete (and probably easier) ones?

Apart from personal interest, there are some good objective reasons that validate our approach. First, though some investigators have attacked the problem from related points of view (13,14), they have used different tools and had a different purpose in mind. In the second place, and this is more important, we are trying to study the aspect that undoubtedly will change less in the future and that, as such, will very likely become the real bottleneck within a few years. This aspect is man who, though adaptive and variable to a certain extent, has definite limitations and constants from both a physiological and a behavioral point of view. They will assure a reasonable long-term validity to the corresponding studies, as opposed to those based on computer characteristics and capabilities, bound to be rapidly obsolete with the fast evolution of computer technology.

Some investigators as qualified as Licklider (15) have expressed doubts about the possibility of basic studies on interaction where the computer is a major factor, because of the rapid evolution in the field. This objection does not apply to our approach, as independent as possible from computer technology, and on the contrary validates it because it shows that man will constitute to a higher and higher degree the limiting factor in man-computer achievements.

We believe there is need at present for this study. Very little has been done to formalize our state of knowledge about the interaction of man and computer, particularly from a quantitative point of view. The use of models and the results of experiments which models suggest will help to isolate critical factors, to point out some possible absolute limitations, and, ultimately, to design better man-computer systems.

Before proceeding, let us state some restrictions in the scope of this paper. We will not be referring to problem preparation, selection of tools (language, computer facility), or basic implementation, i.e., programming and coding; we may be concerned with these activities only when they are done on-line. In man-computer partnership, there are situations in which one of the partners simply transmits information to the other, with no feedback; we shall basically discard this case, in which no real interaction is involved.

Figure 1 illustrates the next restriction. Man-computer interaction essentially involves communication, elaboration and exchange between two information structures, that of the human operator, and that accessible through the computer system. If this is an active two-way communication, there must exist an evaluation, decision and control module directing the interchange. This task may be done by the HO, by the computer, or by both together; in this way three possibilities for positioning the interface in Fig. 1 are established. Scientific and engineering conversational on-line usage of a time-sharing console is an example of the first case, together with on-line debugging, conversational information retrieval, etc. Examination programs in which the computer is in control and makes the decisions are an example of the other extreme case. Symbiotic decision making in civilian and military applications (16,17) is an example of the intermediate case, probably the most interesting but the most difficult to analyze. In this paper we limit ourselves to the case in which the evaluation, decision and control module is on the HO side of the interface, i.e., the interface is in the lowest possible position in Fig. 1.

This figure also illustrates the relationship of man-computer interaction with what can be called "the outside world." The computer may be directly related to it through sensors and/or controls, though in general it is the man who provides that link. In some cases, that outside world may interact with the evaluation, decision and control module, as happens in externally monitored and controlled computer-aided instruction systems. In the following we shall neglect all these exchanges with the outside world, in order to concentrate on the man-computer interaction per se.

To summarize, we are interested in the interaction between the man and the computer, in situations in which the HO is in control and makes the basic decisions while probing an information structure explicitly or implicitly contained in the computer. In this sense, let us point out that it is possible to consider most tasks in an on-line usage of a computer as information retrieval processes. The HO desires information about a program in debugging, about complete files or particular entries in a library search, about relations among variables in most scientific problems, about effects of changing parameters (in the broad sense of the word) in computer-aided design. The idea of dealing with an information retrieval problem will play an important role in the model to be presented in Sections II and III of this paper.

II. OBSERVING MAN AND COMPUTER INTERACT, AND MODELLING THIS INTERACTION

Let us briefly observe and freely interpret what the HO usually does in front of a computer console. In the broadest sense of the phrase, he has some problem or set of problems he wants to solve in partnership with the computer. In a somewhat different sense, he is trying to obtain information about something with the help of the computer, that is, to use it to diminish his uncertainty about some problem. This represents an expected gain for which he is willing to pay a price in terms of his own time and effort while sitting at the console, as well as in terms of computer cost. The informational characteristics of his task apply to the vast majority of cases, be they debugging, information retrieval per se, engineering and scientific applications, business uses, etc.

The HO usually approaches the console with a plan of work, be it broad and sketchy, or detailed and specific. This means that he has a series of tasks to be done at the computer, apart from some other tasks elsewhere he is willing at that time to postpone. In other words, he has a set of priorities which are going to be altered in different ways as his work progresses, and which are dependent on the facility he is using and the operating conditions (response time and other factors in a time-sharing system) at that particular time. In this sense, if his role at the console is not very demanding, he may choose to time-share himself by doing some concurrent task: read a book, work on another problem, or even, as has happened several times to the author, work simultaneously on more than one time-sharing console. Most of the time, however, the computer is much faster than the human counterpart and demands all his attention, the basic reason for time-sharing the computer.

By observing a typical on-line computer user, one soon realizes that there are essentially two modes of interaction. In the first one, the HO just reacts in a reflex mode to some action by the computer; in this case, he has decided in advance what to do in that situation, has pre-programmed himself (his action could be replaced by a computer instruction or subroutine, depending on the case), and is merely reacting in a predetermined way to the stimulus. Though a substantial number of the HO actions are of the former type, the second case is by far the most interesting. In this case, the HO takes an action only after an evaluation is performed and the best available alternative is selected. The HO observes some computer output, and evaluates it, considering the alternative between proceeding with the next step in his plan or altering it. In this, he makes use of some general criteria, but has no definite detailed program for his reaction since he was uncertain about the outcome of his previous run.

In this type of decisions, we postulate that the HO is, probably unconsciously, balancing costs. He has presumably obtained some gain in information* in his last computer experiment (though there may be a loss, these concepts will be precised later). Typically, however, he has not completely removed his uncertainty. He must decide if he proceeds, trying to eliminate that remaining uncertainty, or declare himself satisfied and go to something else. In this he is balancing two costs: the cost that the uncertainty

* Information is being used in this context in a rather loose sense and not in the information theory one.

represents to him, versus the cost in computer time and his own time of making another run in order to keep on improving his information about the problem. There are some subtleties in this; for instance, in his own cost he must include the cost of postponing other tasks in his schedule.

It must be said that the HO is usually interested in some definite aspect of his problem. He selects to perform the tests or runs that have the highest expected gains in information in terms of the aspect he is then concerned with. Full information about the problem lies in the computer state together with the set of states under all possible inputs. To a command, the computer returns some output which represents some symptoms about the problem the HO is trying to diagnose. From those symptoms, the HO must extract the information in terms of his own problem. He then evaluates this information: first he usually compares it with his expectations in terms of an internal model of the problem or situation to see if "it makes sense"; if not, he may decide to investigate why, proceeding along a lateral path and storing his original problem in a push-down manner. As a consequence of that evaluation (the decision process which we postulate is based on a cost estimation), he may decide to continue or stop. If he stops, he must be estimating that the expected gains in continuing do not offset the costs therein involved. He may stop either because he is reasonably satisfied, or because the approach he is taking seems fruitless and he wants to re-examine possible alternatives. In any case, he is trying to optimize, according to some subjective measure of cost, the expected returns of his next action (or action sequence).

Some examples may illustrate the points we have made. Let us first consider the case of debugging. This is a problem-solving task that may be considered also as an information retrieval one.

The program that the HO is trying to debug is resident in the computer. The outcome of any given experiment using that program depends deterministically on both the program itself and the other inputs (data or commands) given to the computer by the HO. To take a rather trivial example, suppose that he wants to determine first if his program will run to completion under all possible circumstances. To find this, he plays some typical experiments. The outcome of these experiments is not a direct answer to his problem, or even a full representation of the state of the program. Typically, for each experiment he will obtain a result (which may be an error message) which is just a "symptom" of the state of the program, a representation of it. On the other hand, each experiment implies a cost, because of time and effort involved, and also because the experiment may alter, perhaps irreversibly, the current conditions.

Before beginning to debug, the HO has some opinion of the chances that his program will run to completion under all circumstances; in other words, he assigns to it some subjective probability. After each run, he re-evaluates it, till he is reasonably convinced one way or the other (if the program does not work, he will then switch to an error search phase). Assuming that he is "reasonably" convinced that the program will run in all cases, what does this really mean? We may say that it reflects his opinion that it is not worthwhile to test any longer. In other words, his expected subjective cost of running more tests is higher than his expected gain in information through them.

In an error search phase in debugging, the HO may do essentially the same thing, except that now, very likely, his hypothesis space will be much more complex. He will assign probabilities to these hypotheses, re-assess them after observing the results of experiments, etc. If none of them seems true, he may have to look for new ones, in a re-examination of his hypothesis space.

One common case in debugging is to answer the following question: are the results being obtained, seemingly correct, really so? Let us take a precise example to illustrate this. Suppose we have programmed a digital filter, and we want to test it. We select some typical input of which the output is known, and use it as an input to the computer to check our program. Suppose that the output must be the values of the function $3 \sin^2 t/t^2$, and we obtain, for $t = 0$, 2.9997 instead of exactly 3 (and similar results for other values of t). Considering quantization noise, etc., we will probably be satisfied. This means that we will consider it more costly to keep on testing, than the minor uncertainty left.

III. A TENTATIVE MODEL ON MAN-COMPUTER INTERACTION

In Section II of this paper we have presented in an informal fashion most of the basic ideas involved in our model. Now we begin to formalize them. For didactical reasons, we shall describe the model at two levels, first in a very simplified way, next in more detail.

Figure 2 presents a simplified block diagram of the model. The computer system and the information structure accessible through it are represented by the lower box. At each time, t_1, the computer is characterized by a state vector $\underline{x}(t_1)$ which is a description of the system with which the HO is interacting. In Turing Machine terms, $\underline{x}(t_1)$ is a full description of the machine at the present time, i.e., set of states, set of instructions, tape alphabet, initial (present) state and head position, and set of final states. The HO is generally not interested in such a precise and detailed description (though in some special cases -- particularly in debugging -- he may be interested in the detail of some registers, and any of them may qualify). He is interested in a higher level description of the state of his computation and task. This is reflected in the HO internal model of the situation which is a problem-oriented description with irrelevant aspects and details removed. This internal model is part of the HO information space.

The two other boxes, labeled Evaluation and Decision, also correspond to the HO. A command can be represented by a vector $\underline{u}(t_i)$, and can include instructions and data fed into the computer. This vector (corresponding to an input tape in a Turing machine model) actuates over $\underline{x}(t_i)$ modifying it to a new vector $\underline{x}(t_{i+1})$. In correspondence with this modification, the computer produces some message described by another vector $\underline{y}(t_{i+1})$ from which the HO extracts the information $\underline{z}(t_{i+1})$ relevant to his problem. This information, together with the output of the internal model, is fed into the Evaluation module, in order to update the estimation of the validity of the hypotheses formulated about the problem being solved. This estimation may be represented by a probability vector $\underline{p}$. Given a prior probability assignment $\underline{p}(t_i)$, and the computer output $\underline{z}(t_{i+1})$, the HO is assumed to computer the posterior probability vector $\underline{p}(t_{i+1})$ in a Bayesian way, as will be discussed later.

Next, an estimation by the H f the gains made by the previous run, in terms of information obtai ed about the problem that motivated the run, is made. This "state of knowledge" about the problem (to be defined more precisely later) is transmitted, to the Decision module where a decision is taken as to whether the present task should continue with a new command, or otherwise terminate it. The latter is done when an estimation of the cost of continuing yields higher values than the expected reduction in uncertainty. In this case, a new task may be undertaken. Another possibility is for the HO to find that with his former policy he has not succeeded in reducing his uncertainty to the desirable extent. In this case, a reformulation of policy must follow, that is, generation of new hypotheses and/or actions.

Operation of the model is started by means of an initial computer state $\underline{x}(t_o)$ and an initial estimate $\underline{\rho}(t_o)$ in terms of the HO desired informational result space. Successive feedback loops are performed during each task. At the completion of a task, and always according to our model, results are stored by the HO for future reference.

A more detailed block diagram of the model is presented in Fig. 3. Following our stated purpose, we concentrate on the human side of the interaction. The two modules labeled Decoder and Encoder represent the necessary transformation of signals between the HO and the computer information spaces (of course, if a symbolic language is used, there are other translations inside the computer system). The connection between Decoder and Encoder corresponds to the already mentioned, and trivial, pre-programmed interactions.

The Decoder converts the computer output $\underline{y}$ into the message $\underline{z}$ in which the information irrelevant in terms of the present context has been eliminated. In elementary cases, this decoding could have often been programmed in the computer; for example, the HO may receive the message $a = 2.3957$ while being only interested in the sign of a. In other cases, complicated pattern recognition processes may be involved.

The Encoder, in turn, transforms the selected action into a set of control messages sent through the interface.

In Fig. 3 the HO Information Structure has also been defined in more detail. The Temporary Storage serves as an I/O buffer for the information exchanged with the computer system. It is connected to a Permanent Storage which is part in the HO's memory and part in the form of hard copy produced by the computer, notes, etc.; it acts as a file system relevant to the problem on-hand.

The main component of the HO Information Structure is (in terms of our model) the Internal Model module. It contains the estimated representation $\underline{\hat{x}}(t_i)$ of the problem under solution. This state vector $\underline{\hat{x}}$ is related but not identical to $\underline{x}$; it is a more concise, weighted version of the latter, and may include other pieces of information not present in $\underline{x}$ such as constraints related to the nature of the problem, past experience, etc.

Depending on the point of view which one may want to take, $\underline{\hat{x}}$ can be considered a noisy representation of $\underline{x}$ or vice versa. In any case, the following functional relationships can be established for the computer:

$$\underline{x}(t_{i+1}) = f[\underline{x}(t_i), a(t_i), t_i] \tag{1}$$

$$\underline{z}(t_{i+1}) = \underline{g}[\underline{x}(t_i), a(t_i), t_i] \tag{2}$$

With simple minor alterations we could have $\underline{f}$ instead of $\underline{z}$, and $\underline{u}$ instead of a. For the internal model we have:

$$\underline{\hat{x}}(t_{i+1}) = \underline{\hat{f}}[\underline{\hat{x}}(t_i), \hat{a}(t_i), t_i] \tag{3}$$

$$\underline{\hat{z}}(t_{i+1}) = \underline{\hat{g}}[\underline{\hat{x}}(t_i), \hat{a}(t_i), t_i] \tag{4}$$

It must be seen that we may be confronted with errors -- noise -- at all levels. For example, the control really effected may be different than that intended at a logical or at a manyal level (typing error).

The last important module in the HO Information Structure is the General Plan and Strategy one. This receives inputs from the Internal Model, from the Results Evaluation (costs), and from the rest of the HO's memory which includes information that is mostly irrelevant (or apparently so) to the precise problem on hand. From the complex information structure, hypotheses and actions are generated. The set of possible actions {a} is in the model evaluated in a Utility Evaluation module. The output utilities -- or their negatives the costs {J(a)} -- are derived from both the expected informational gain after the action and the expected cost of the action (mainly in terms of computer and human time).

The utility set {C(a)} complements an informational measure $M[\underline{p}(t_{i+1})]$ which is an index of the difference between the presumable goal of no uncertainty, and the current state of information about the problem on hand. In other words, the posterior probability vector $\underline{p}$ is used to compute a scalar measure M of the HO's degree of "knowledge" about the informational problem he is trying to solve. This measure M, to be discussed in Section IV, is basic to compute the usefulness of the work just done, in preparation for the decision about future actions. That usefulness is established for past actions and estimated for future actions in terms of a general cost J, which is in turn the sum of two costs: K, representing the cost of not having perfect knowledge about the problem, and a function of the informational measure M, and L, which is the cost of performing the computation. These costs will be further analyzed later.

The posterior evaluation of M decides if the current strategy should be changed. This may be caused by a lack of results, which may be as bad as to originate an increase in uncertainty from before to after last experiment performed. When uncertainty has become very large, or no satisfactory progress is being made, the model postulates that a change in the HO's policy will occur. He will do this by one or more of the operations:

1. Select new action and action sequence (without changing the action set);

2. Redefine action set (control set);

3. Redefine event set (hypothesis set).

The first one represents the milder change of the three, while (3) represents a major re-examination of the problem.

If the HO operator decides not to change his strategy, he goes on in the model to decide if he should proceed with a new command of the same type as before. It is assumed that the HO does so by means of a prior evaluation of the informational measure M (which now corresponds to time t_{i+2}) which he then in turn uses to evaluate his expected cost after the prospective experiment. The decision to proceed is made in terms of this cost. If the HO decides to proceed, the control signal corresponding to the proposed action is issued, encoded, and the cycle has finally closed. If the decision is not to proceed, a given hypothesis is accepted (remark that it most likely corresponds to a probability of less than 1, the reason for accepting it being the cost analysis). At this point, this result is put into temporary storage, and control is passed to the Strategy module which will indicate what to do next.

IV. DISCUSSION OF SELECTED ASPECTS OF THE MODEL AND POSSIBLE ANALYTICAL APPROACHES

In this section we shall discuss some aspects of the model in further detail, and at the same time evaluate the merits and disadvantages of different analytical approaches to it.

A. An Optimal Control Theory Approach

It is possible to formally consider the model on man-computer interaction under the framework of modern optimal control theory (18,19). The optimal control problem can be stated as: Given a dynamical system (defined by state and output equations), a set

U of admissible controls $\bar{u}$, a target se' S, and a cost function J, determine the control function $\underline{u}$ in U which minimizes J. We could give a parallel definition of an "informational control problem" by means of the following elements:

a. A sampled, discrete, on-line computer system defined by Eqs. (1) and (2) above.

b. A set U of all possible <u>experiments</u>, satisfying the constraint $\{U_t\}$ which is a language defined as the set of <u>admissible commands</u>. Supposing that $U_t \subset R_m$, $\underline{u}(\cdot)$ satisfies the constraing $\{U_t\}$ if $\underline{u}_t \in U_t$ for all t.

c. A <u>target point</u> S_o and/or a <u>target set</u> $S \subset R_n\ X(T_1, T_2)$ here T_1 and T_2 are respectively the initial and final times. In the man-computer case, the target set must be defined in terms of an informational measure, representing the uncertainty about a problem. A measure, though not a distance, is the entropy H; a threshold of acceptability H* must be defined in order to define a target set S.

d. Two real-valued <u>cost functions</u>: $\ell(\underline{x}, \underline{u}, t)$ representing the cost of executing the computation, and $K(\underline{x}, t)$ which represents the cost at the end of the computation, and, as such, is related to the remaining uncertainty. Really $K(\underline{x}, t) = F[M[\underline{p}(t_f)]]$. Then, if we get to the target set S, in time $t_f - t_o$, we define the <u>total cost function</u> J as

$$J(\underline{x}_o, \underline{u}, t_o) = K(\underline{x}_f, t_f) + \int_{t_o}^{t_f} \ell(\underline{x}_u(T), \underline{u}(T), T)\, dT \quad (5)$$

Then, the optimal man-computer control problem is:

Given the elements (a), (b), (c), and (d), i.e., a sampled, discrete, on-line computer system, a set U of possible experiments leading to admissible commands $\tilde{u}$, an informational target point and/or a target set, and a cost function J, determine the command string $\underline{u}$ in U which minimizes J.

The analogy presented above should be treated cautiously. Unfortunately, problems involving the HO as a controller, and more so, as a decision maker, are hard to state in precise quantitative terms. We must also remember that our model cannot be a deterministic one, since most of the parameters and functional relationships are uncertain to man. This in a way parallels the presence of noise in real dynamic control systems. In both cases, one is dealing with probability distributions of which expectations must be taken. Another important problem stems from dealing on-line with a discrete state computer system. Research is, however, in progress (20,21) in an attempt to find common grounds between Control Theory and Automata Theory.

B. A Decision Theory Approach

Further insight can be obtained on man-computer interaction by studying how the model described in Section III is related to a formulation in terms of Statistical Decision Theory (22,23). We must be careful in our statement of the problem if we want to avoid some confusions. The typical decision problem is a sextuple set $\{e, \tilde{z}, a, \tilde{\theta}, u(e, \tilde{z}, a, \tilde{\theta}), P_{\theta,z|e}\}$ where e is an experiment, z is its outcome, a is an action, $\tilde{\theta}$ is the "state of the world," u is the utility function (assessment of preferences),and $P_{\theta,z|e}$ is the probability assessment of outcomes. To behave optimally, the decision maker (DM) should choose an e and then, having observed z, choose an a, in such a way as to maximize his expected utility. This means that in this formulation one seeks information through an experiment e in order to later perform an action a that leads to some consequence u.

The Decision Theory scheme can obviously be related to the behavior of the HO in front of a computer. We should be cautious, however, since our problem presents some unique and interesting aspects that may force a special treatment.

In Decision Theory, one is interested in selecting the possible action that would yield, under given circumstances, the maximum utility to the DM. With this purpose, the DM may perform experiments to improve his information and correct his prior probability space. In the specific man-computer decision problem, the ultimate goal is to obtain information, and one should not confuse the gain in information in the usual decision problems -- when an experiment is made as an auxiliary item -- with information to be obtained as an end in the man-computer case. (Of course, in a completely different level, the information obtained at the computer will be eventually used to decide on some other action, but we are not interested in this.) The HO sitting at a computer console does not usually perform experiments to decide what actions he is going to take at the same console (though under some circumstances this may be the case). He is usually in the Decision Theory case of no intermediate experiment, that is, no e and no z.

The utility function is now a function of the informational gain. It is in fact the negative of our total cost J of Subsection IVA.

Of course, most man-computer interactions could be characterized as sequential decisions rather than single ones. But again, the particular characteristics of the man-computer interaction introduce some complications. The most important one relates to the selection of alternatives. This applies specifically to the selection of actions, although a similar discussion will be done,applied to hypotheses being tested, in Subsection IVD. Most frequently, the set of alternatives is not closed, but open. To simplify matters -- and many times this may be an oversimplification -- the set of alternatives is often presented as closed, this being one of the postulates in which Decision Theory is based. In this context, closed means a set that includes all possibilities; they are collectively exhaustive. On the contrary, an open set means one that does not exhaust all possibilities.

Although the closed approximation may be correct in other applications, it seems rather restrictive to our man-computer interaction. In each command, decisions will be made based on a closed subset, but if no good results are obtained, a search for new actions may be originated, as was stated before in presenting our model. The HO working on-line is frequently modifying and restructuring both his hypothesis and his action spaces. The sudden insight into the solution of a problem is just an extreme example of this.

In Decision Theory, an important point is that the posterior probability can be obtained in either one of two ways:

1. Direct estimation, the same way as the first of the chain of successive priors was itself estimated.

2. Computation through the use of Bayes' Theorem:

$$P(\Theta_i | z,e) = \frac{P(\tilde{z}|\tilde{\Theta}_i,e)\ P(\Theta_i)}{\sum_i P(\tilde{\Theta}_i)\ P(z|\tilde{\Theta}_i,e)}$$

The basic assumption of the Bayesian point of view is that the DM is willing to act as if both methods for obtaining the posterior probability should yield the same result. Thus an approximation to the HO's behavior in decision making can be based, among other things, on the assumption that the passage from prior to posterior probabilities is done according to Bayes' Theorem. Edwards (24,25) has investigated this and related topics. His experiments seem to indicate that man changes his opinions in the presence of experimental results or generally new information, less than what Bayes' Theorem indicates. In other words, man profits less from recent information than he should according to the Bayesian model. This phenomenon is what Edwards has called "conservatism." In our model we have adhered to the Bayesian point of view, but conservatism could be easily incorporated, if desired, to yield more realistic results.

It is probably here a good place in this paper to point out the analogies between our approach to man-computer interaction and Gorry's work on diagnosis (26). He discusses, with a different purpose in mind, some problems of interest to us. Among them are the problems of look-ahead, estimation of the utilities of different decisions, and pruning the decision tree in depth and for breadth. We are faced with similar problems and we must say that we believe that the HO in his interaction with the computer does not perform any complete computation as Decision Theory and Bayes' Theorem would suggest. That would be an optimal policy, useful to be compared with the actual performance of humans which must be based more in subjective estimations than in mental calculations.

C. The Problem of Costs

Let us now look closer at the costs as defined before. An analysis of the effects of response time on the HO's estimation of costs has been recently presented by Carbonell, Elkind and Nickerson (27). For simplicity reasons, let us make the notational definitions:

$$L = \int_{t_o}^{t_f} \ell(\underline{x}_u(T), \underline{u}(T), T)\, dT \tag{6}$$

$$K = K[\underline{x}_f, t_f] = F[M[\underline{p}(t_f)]] \tag{7}$$

Our total cost can then be written

$$J = K + L \tag{8}$$

How are K and L obtained in the case of man-computer interaction? As said before, the cost K depends on the remaining uncertainty after the run. Let us postpone further study of K till the next subsection, and consider the "trajectory" cost L. Two main components appear for it, namely the computer cost and the HO's cost. In a time-sharing environment, computer cost depends on the way computer services are charged. One or more of the following measures are used: hook-up flat charge, console elapsed time, CPU time, memory usage as a function of space and time, special facilities used, communication link, etc. Without much loss of generality, one can say that the computer cost is of the form

$$L_c = a_o + \sum_j a_j t_j \tag{9}$$

where the t_j's are the times corresponding to the different resources, the a_j's are the corresponding unitary prices, and a_o corresponds to the hook-up charge.

In few cases, the HO will estimate the cost of his time as proportional to the time elapsed during the computation. There are two factors in this. One is his "cost" as a scientist, programmer, etc., to be derived from his salary. A more important one, perhaps, from a subjective point of view is the cost that his present activity represents to the HO in terms of postponing other activities he could be doing at the same time (28,14), and that are queuing for his attention.

When we want to estimate the subjective cost L_{HO} which the man assigns to his own time, in a first approach we might incorrectly assume that L_{HO} is proportional to the elapsed time t_e. This is not so for several reasons.

First, we have a limit in the total availability of time of a given man, both to himself and to his organization. As an upper bound is approached, higher incremental unitary costs must be placed on his time.

There are many cases in which additional time constraints are imposed upon the HO at a computer. We have all experienced the effects of having been assigned on-line time at a computer for, say, 1 hour at the end of which another user is due. In this case, as time approaches its end, and if the schedule of tasks has not been exhausted, pressure builds up to perform fast and efficiently the most important tasks. The cost of performing one computation increases because we may run out of time to perform any other task. In a more dramatic environment, such as an on-line military system, an on-line spatial control station, or a real-time MIS, a man at a computer may only have a few minutes to perform some computations, which would become completely useless if results are obtained after a given deadline.

In general then, the operating cost can be written as:

$$L = \phi(t_e, t_a, t_r, \{t_j\}) \tag{10}$$

where t_e is the elapsed time during the computation, t_a is the HO's total availability (per day or per week), t_r is the remaining time in the cases of externally limited time, and the t_j's are the resource costs. In a recent paper, Carbonell, Elkind and Nickerson (27) have discussed possible analytical forms for Eq. (10).

In the discussion above, our model has assumed that costs could be obtained in a deterministic way. Apart from uncertainties due to incomplete knowledge by the HO of cost variables and functional relationships there is the main question of uncertainty about times. An operator that does not know what the cost (in the general sense of the term cost) of a given computer run is going to be to him, will be in a much worse position to make good decisions, than one who can estimate those costs with a fair degree of precision. The reaction of people to computer systems operations usually takes this into account as a fairly important factor. It has been observed (29) in a time-sharing environment the preference of users for a fixed delay versus a possibly shorter but variable one. Furthermore, if the mean and variance of the distribution of variable response times are known, conditions are better than when they are unknown. People particularly dislike unpredictable conditions. If delays were long, but predictable, they could conceivably carry on some other activity instead of wasting time waiting for a possible result that may come now or later. In terms of our model, if people can predict times, they may devote themselves to some other activity, thus diminishing their own cost. Furthermore, they could make fairly precise cost estimates and confidently derive decisions from them.

Before ending this discussion on costs, let us look again at Eqs. (6), (7), and (8) and make a few remarks about them. First, to the case of the HO inputting information into the computer, and editing it, we can assign the value $K = 0$ (null terminal cost) since no information is then sought out of the system. In that case, we just want to minimize L, the "trajectory" cost. Next, let us note that in time-sharing, the running cost ℓ depends directly on T, since the response of the system will change with time (different loads); really it is the state $\underline{x}$ of the computer system which is then explicitly time-dependent. In an on-line unshared use of a computer neither $\underline{x}$ nor ℓ are explicit functions of time. We can also consider that in time-sharing ℓ is a time-independent random variable because of its dependence on an unpredictable load. This is not only true for costs dependent on elapsed time, but it may also apply to CPU and memory costs as well (e.g., different page turning in two different instances of a given fixed computation).

D. Some Informational Aspects

We have already said that our model for man-computer interaction is based on the idea that most interactive tasks are some form of information retrieval. In the model the HO extracts in the Decoder from the output $\underline{y}$ of the computer the relevant information $\underline{z}$, and then uses it to obtain his posterior probability vector $\underline{p}$. These probabilities refer to hypotheses the HO has made about a problem, in what we might call his belief space (30). This space may consist of only two alternatives, if he is only checking if something happens or not (like a program running to completion under all possible inputs within a set). In other cases, such as a search for some "bug" in a program, the HO may have a set of hypotheses with probabilities p_j, $j = 1, 2, \ldots q$.

It is interesting to note the reduction in information that normally occurs from the total description of the state of the system given by the state vector $\underline{x}$ with m dimensions, to the output vector $\underline{y}$ with n dimensions, to $\underline{z}$ with r dimensions, to the probability vector $\underline{p}$ with q dimensions. In practically all interactive cases we will have

$$m \gg n \geq r \gg q \qquad (11)$$

As an application, $m >> n$ indicates the impossibility to reconstruct $\underline{x}$ from $\underline{y}$ alone. The fact that $n > r$ may not be a disadvantage. In a real situation, though not in the model, the HO may often use the observation of $\underline{y}$ to extract information about other aspects related to tasks to be performed later, apart from the main processing in terms of his current interest.

Let us now try to answer the question as to whether the hypothesis space is open or closed in the sense discussed before in this paper. In the situations described above, we must consider the hypothesis space as an open one, in the sense that to all definite hypotheses one must add what we may call the complementary one, that is, the hypothesis H_o that "something else" is happening.

We postulate that the HO assigns to this possibility of "something else" happening some probability p_o. Therefore

$$p_o + \sum_j p_j = 1 \tag{12}$$

which indicates that the sum of the p_j's will usually be less than 1.

From an Information Theory point of view, the complementary hypothesis is just another hypothesis as all others, and p_o is not differentiated from the P_j's. We claim, however, that this is not the case from a subjective point of view. In most cases, the HO will use p_o in a way different from that in which the other probabilities are used. If the complementary hypothesis turns out to be true, the HO finds himself completely ignorant of what is happening, except in a negative way, i.e., that all other hypotheses H_j that he has considered are false.

To illustrate this point more clearly, consider the case of debugging in which hypotheses about the cause of some "bug" are made by the HO. There is also some chance (p_o) that the cause be something else. The HO performs some tests, successively re-evaluates his vector $\underline{p}$, and finds himself after some time in the position that the updated p_o has become dominant, even to the point that what started being the complementary hypotheses is now certain, none of the other hypotheses being possible. It is important to notice that the HO is still fully ignorant about the cause of his problem; he has gained very little knowledge about it.

What to do when the complementary hypothesis becomes dominant? We postulate that the HO will look for new alternatives, new hypotheses, and thus claim that the increase in p_o beyond a threshold may be a triggering mechanism to enter the search-for-hypotheses mode.

The capability of generating alternatives, both hypotheses and actions, is of paramount importance and one of the most difficult problems in modeling human behavior. It is conceivable that a hierarchy of associations defined according to some distance (that may be related in a heuristic way to frequency and importance of use) could be established. The original set of alternatives would be based on the shortest links. Regeneration of alternatives would try longer paths. A similar behavior has been suggested to explain the resolution by man of grammatical ambiguities in natural languages (31).

According to our previous discussion, the probability vector $\underline{p}$ really represents (after Roby (30)) the belief state of the HO about his problem. Roby study assumes in general that the states are mutually exclusive and (collectively) exhaustive, and therefore the set of associated probabilities sums to one. We have shown before that this is not the usual case for the man-computer interaction, in which the probability p_o of the complementary hypothesis should be treated in an independent way.

The above discussion becomes clearer if one tries to derive from the probability vector $\underline{p}$ a scalar measure M to characterize the knowledge that the HO believes to have about his problem. Information Theory provides the entropy H

$$H = - \sum_{j=0}^{q} p_j \log p_j \tag{13}$$

This measure is based (32) on some conditions that it was found desirable for it to fulfill: (1) H should be continuous in the p_i. (2) If all the p_i are equal, $p_i = 1/n$, then H should be a monotonic increasing function of n. (3) If a choice be broken down into two successive choices, the original H should be the weighted sum of the individual values of H. With these three assumptions, Shannon (32) proves that the only H satisfying them is proportional to the value given by Eq. (13), the constant of proportionality merely amounting to a choice of a unit of measure.

The entropy as defined above fails, however, to take into account some informational aspects that are quite relevant from a behavioral point of view. One of them is the value of information, or the equivalent cost of uncertainty. Howard (33) has recently discussed its implications from a strict Statistical Decision point of view. In simple words, not all uncertainties represent equal costs to us.

The entropy also fails to make any distinction between the regular hypotheses and the complementary one. More precisely, if the complementary hypothesis becomes true (the HO is still fully ignorant about what happens) the entropy goes to zero, the same as when one of the regular hypotheses is true. If $p_o = 1$, we have reached certainty, yes, but in subjective terms, certainty of knowing practically nothing about the problem.

One should not, however, criticize Information Theory because of its failure in explaining the subjective belief of the HO operator about his own knowledge. Rather we should criticize ourselves for trying to apply Information Theory outside its domain of application. We must bear in mind that Information Theory was originated to deal with the transmission of information with a defined, closed, set of alternatives.

At this point, it seems necessary to define a new measure M which could be used in our model to represent the belief of the HO in his own degree of knowledge about the problem. The purpose in the establishment of such a measure is clearly to provide a quantitative way to arrive at the terminal cost K, the cost of being off our target, i.e., the cost of imperfect information.

The most rational way to derive such a measure of belief in personal knowledge seems to be the statement of a set of conditions for it to fulfill.

In the following we shall sketch what those conditions may be, as well as some measure that satisfies them. Of course, this is a delicate subject that requires and deserves much more study than we have done up to now. Necessarily, then, what follows should only be taken as a tentative, preliminary approach, and no definite conclusions should be derived.

It will be convenient first from a practical point of view to obtain a measure R corresponding to the belief in lack of knowledge, a measure of estimated "ignorance." We will later derive M from R. Let us suppose that we have an open set of hypotheses to which a HO has assigned probabilities p_j, plus p_o for the complementary one. The conditions or postulates that R should satisfy are tentatively established as follows:

a. The measure R should reach a pre-established minimum R_{min} if and only if one of the probabilities $p_j (1 \leq j \leq q)$ is equal to 1. As a particular case R_{min} may equal 0.

b. The measure R should reach a pre-established maximum R_{max} if and only if the probability p_o of the complementary hypothesis is equal to 1. As a particular case R_{max} may equal infinity.

c. By replacing any of the hypotheses $H_j (j \neq 0)$ by two others H_j' and H_j'' such that p_j' and $p_j'' = p_j$, the value of R should not decrease.

d. If the hypotheses $H_j (j \neq 0)$ are equally likely, an increase in their number without affecting p_o should make R larger. In other words, if

$$\sum_{j=1}^{q'} p_j' = \sum_{j=1}^{q} p_j \leq 1, \text{ and } q' \geq q, \text{ then } R_q' \geq R_q.$$

e. If the number of equally likely hypotheses is unchanged R should monotonically increase with p_o.

f. If a hypothesis H_{q+1} is created such that its probability of occurrence is taken out of p_o, leaving a new reduced $p_o' \geq 0$ (i.e., $p_o = p_o' + p_{q+1}$), and the other probabilities are unaffected, the value of R should decrease.

As said before, the set of conditions presented above is only a tentative one. No effort has been made to make these conditions independent, i.e., non-redundant. Condition (c) needs some discussion. Obviously the HO may have different degrees of "fineness" in establishing his set of hypotheses, and replacement of hypothesis H_j by two others may be thought of as a partitioning process. In a sense, we should not have an increase in R in that case. On the other hand, if we effectively have a substitution of two unrelated hypotheses for a single original one, R should increase. If we want to eliminate the first case, we could talk of levels of resolution, and have our HO always working at the coarsest possible level compatible with his current need to know.

As an example, and without claiming any particular merit for it, let us present a possible measure R and the corresponding M. This measure is based on products of factors of the form $(1 + p_j)$. The motivation for this measure lies in the fact that we want p_o to represent many possible unknown alternatives. So it seems plausible to divide up p_o into r equal intervals Δp_o such that $r\Delta p_o = p_o$. Treating each of these intervals as the p_j's, and letting r go to infinity (or Δp_o go to 0) we have:

$$R = \lim_{r\to\infty} \prod_{k=1}^{r} (1 + \Delta p_o) \cdot \prod_{j=1}^{q} (1 + p_j) =$$

$$= \lim_{r\to\infty} (1 + \frac{p_o}{r})^r \cdot \prod_{j=1}^{q} (1 + p_j) = e^{p_o} \cdot \prod_{j=1}^{q} (1 + p_j) \qquad (14)$$

In this way we obtain a measure R. It can be shown that this measure complies with conditions (a) to (f) as stated above, the proofs being omitted since they are rather straightforward.

It is found that $R = e$ for $p_o = 1$, and $R = 2$ for some $p_j = 1$. From this R it is easy to derive a second measure M of belief in knowledge. For that, for instance, one can apply the transformation

$$M = \frac{e - R}{e - 2} \tag{15}$$

which produces values of M between 0 for no knowledge, and 1 for absolute certainty.

V. CONCLUSIONS

In the body of this paper we have presented a tentative model on man-computer interaction. In this section we present some final remarks and conclusions.

First, let us clearly indicate that we are not at all claiming that a HO actually follows the behavior indicated by the model. It is unreasonable to think that he would compute numerical measures such as M. All we are claiming is that the model may provide a suitable framework to think, talk, and carry on theoretical and experimental investigations about man-computer interaction. The analytical developments in the presentation and discussion of the model are only convenient formulations of constraints and optimal bounds. Men, of course, seldom behave optimally; furthermore, it is questionable if their behavior can be expressed in analytical terms. In Section IV we have presented various analytical points of view (complementary rather than in conflict) related to the model, and discussed their merits and limitations. It seems at this stage that a fully analytical treatment is inadequate for the task because of its rigidity, complexity, and lack of developed analytical tools, unless we want to impose severe constraints and reduce the problem to rather trivial uninteresting cases. On the other hand, an information process model along the lines developed in Section III, and incorporating pertinent elements from the approaches discussed in Section IV, may be the most promising line of attack. In a recent paper Gregg and Simon (34) have discussed in a particular context (a type of concept formation) the merits of an information process model versus an analytical one; they conclude that in their particular case, the process models are to be preferred as being stronger, more universal, more precise, simpler, and provide better predictions than the analytic stochastic theories.

What is the work ahead? On the one hand, a selection of one or more particular applications should be done to test the model and some of its implications; several applications are presently being considered. Next both theoretical and experimental work must be done. Furtunately, because of the modular nature of the model, controlled experiments with human subjects can be conducted on separate aspects, while maintaining approximately fixed conditions on the others. Finally, an overall validation will be necessary at some point; in this sense an information process model could simulate in a computer both another computer and the HO controlling it while engaged in the solution on-line of some class of problems. The results of the comparison of this simulation with observed facts and experimental results about man-computer interaction should be enlightening.

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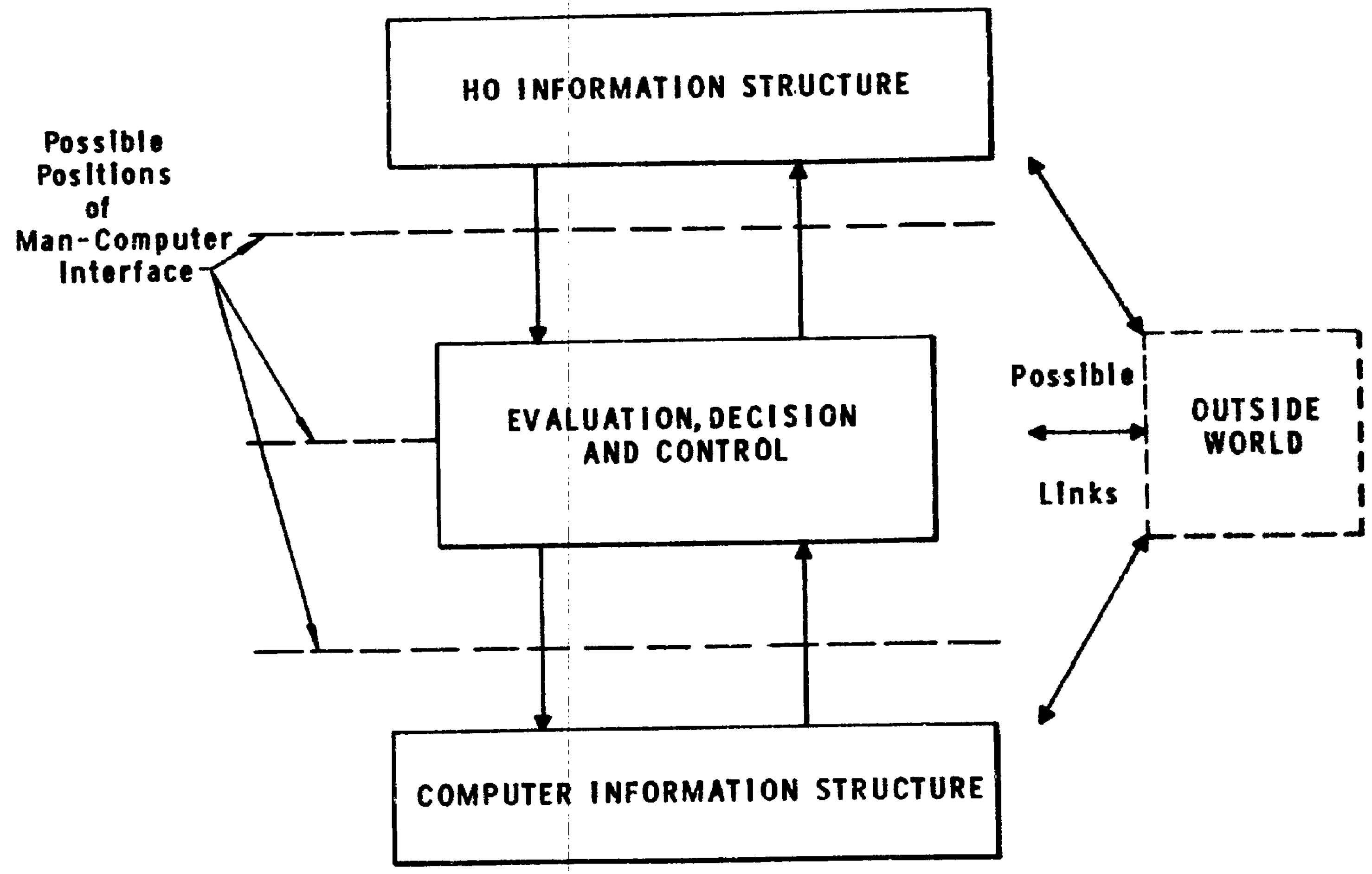

FIG. 1 MAN-COMPUTER INTERACTION PROCESS

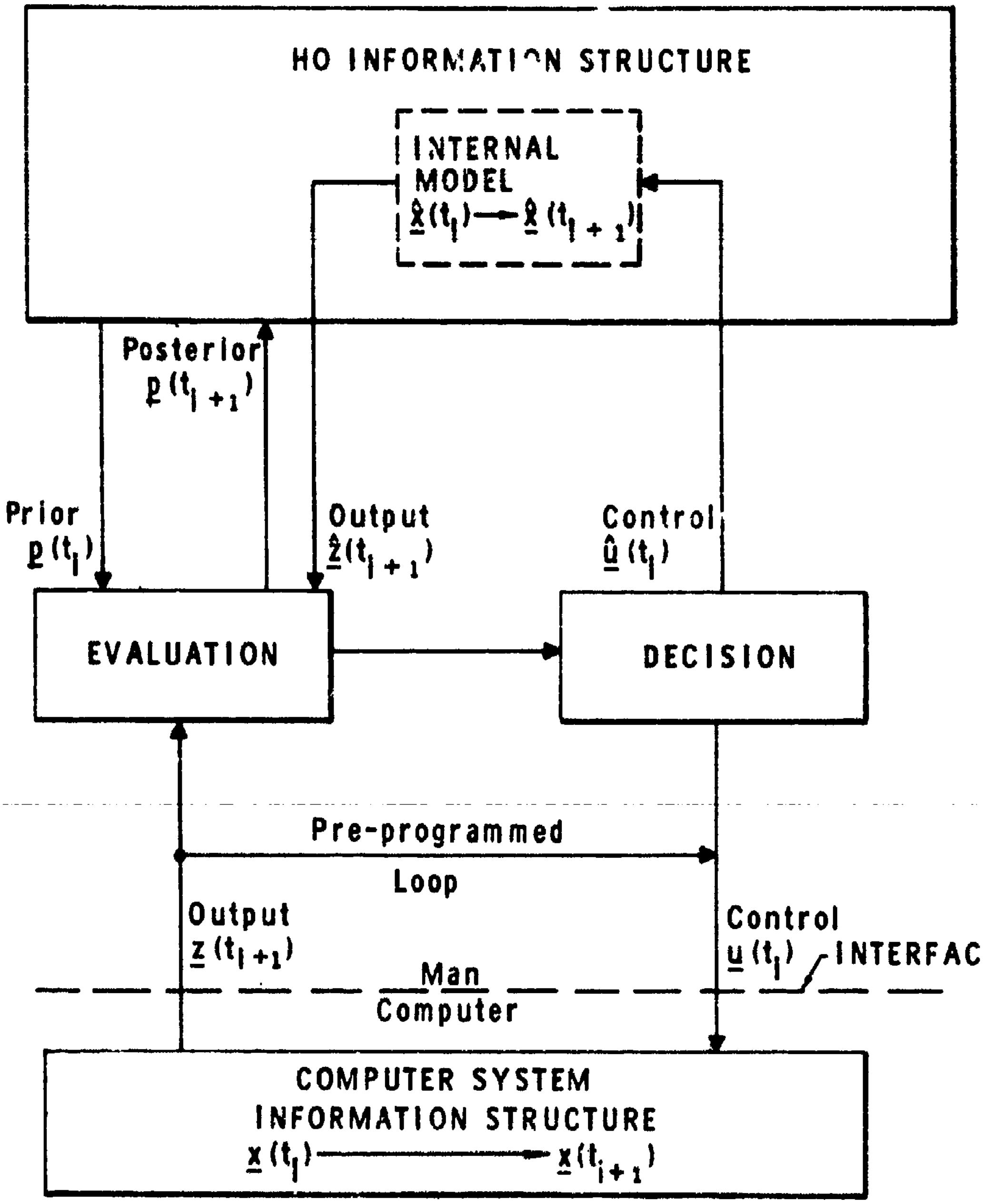

FIG. 2 BASIC ORGANIZATION OF THE PROPOSED MODEL

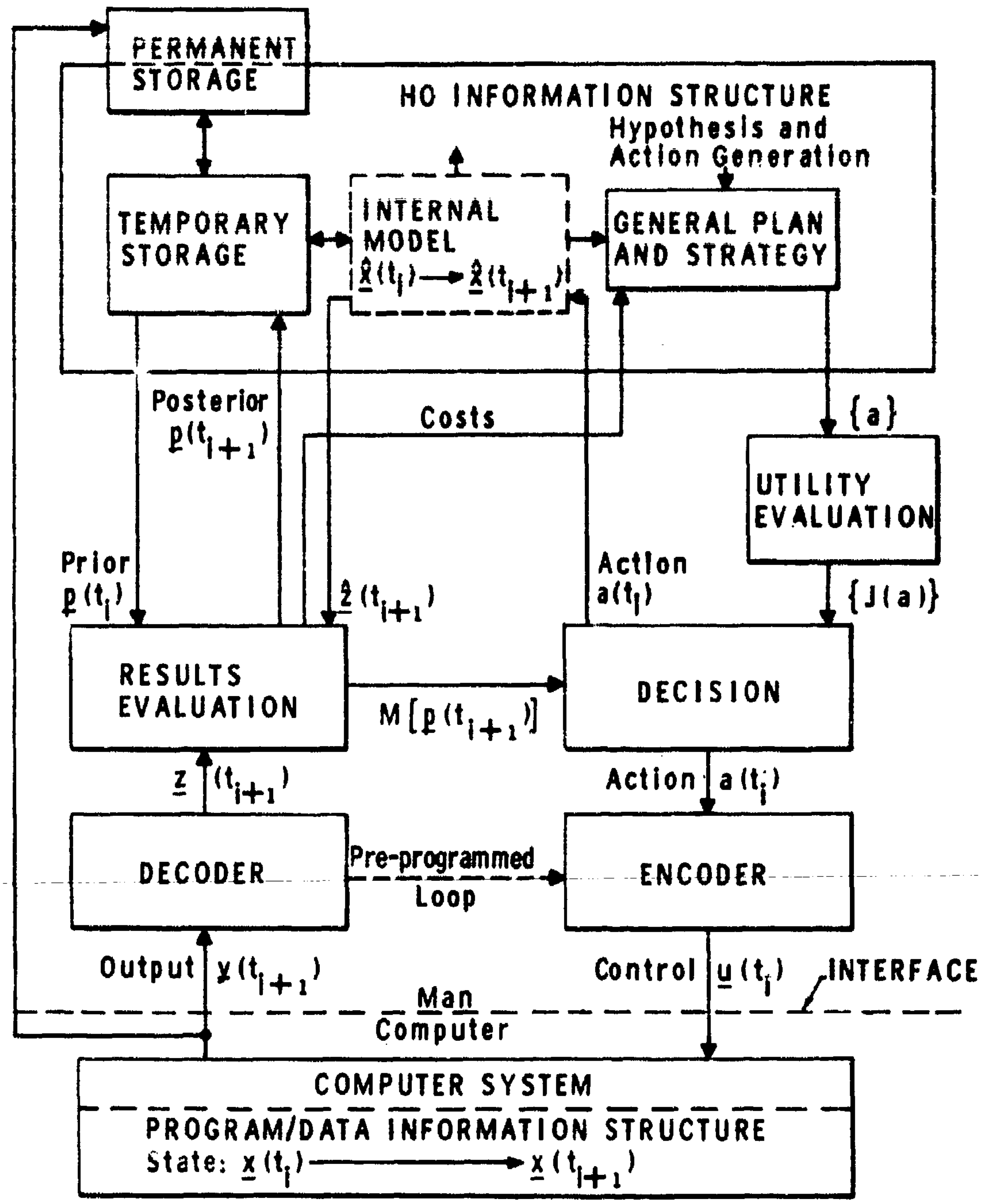

FIG.3 A MORE DETAILED BLOCK-DIAGRAM OF THE PROPOSED MODEL

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13. ABSTRACT

A survey of the literature related to man-computer interaction reveals the many aspects of this problem, which appears to be in the crossroads among such diverse fields as computer languages, computer systems operational characteristics, control theory, decision theory, information theory, applied psychology, computer display and interface engineering, etc. In this paper we have chosen to present the on-line interaction from an information and decision point of view. After a brief discussion of classes of on-line situations and tasks, we propose a model of the case in which a human operator is engaged on-line in the solution of a problem like debugging a program, testing a model in a scientific application, or performing a library search. In this model the human operator is considered to seek to minimize overall cost. This cost is obtained by adding the operational cost of both man and computer to a remnant terminal cost originated by the remaining uncertainty. This analysis, performed for each of a set of possible alternatives for action, may lead to select and execute one of them, to terminate the process, or to re-evaluate the possible alternatives and/or hypotheses in a search for new ones. Some practical applications in terms of response time and other characteristics of a computer utility are presented, as well as some theoretical implications from an informational point of view.

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